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Predicting spikes with artificial neural network

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Dear editor,

Spikes or action potentials are prominent features in most brain neurons, through which neural information can be efficiently processed and reliably transmitted, and eventually form the basis underlying how the brain works [1]. Previous studies have proposed many computational models to characterize the firing dynamics of neurons, among which Hodgkin-Huxley(HH)-type model is the most famous one [2]. HH-type models not only show the highest accuracy in capturing neuronal spikes, but also their model parameters have definite physiological meanings. HH-type model is a set of differential equations which do not have analytical solution, so numerical calculation method such as Euler's method or Runge-Kutta method is used to get the numerical solutions. However, to ensure the accuracy of spike timing calculation, the step size of numerical iteration method has to be very small, such as 0.01 ms. Therefore, the simulation cost of HH-type model is very expensive, especially when modeling large-scale brain networks. One way to speed up the simulation is to take a library-based numerical method [3]. Specifically, a plenty of spike samples from the classical HH-type model under different stimulus intensities have firstly been collected to build a library. When performing network simulation composed of HH-type neurons, spike sequences of the corresponding HH-type neurons can be estimated from the library. However, this method is still not good enough, in that the method can only reproduce raw statistical information of spikes, other than capture the spike timing information of neurons, which is more informative than the raw statistical information. Moreover, they only tested their method using the classical HH-type model. Ionic neuron models have many different types except for the classical HH-type, and firing activities produced by these neurons are rather diverse and changeable, thus, generality of this method to other models is still unknown. Considering the good mapping ability of an artificial neural network (ANN) and the dynamic nature of the HH equations, we explored a new idea of using ANN to help speeding up simulation of HH equations.

In this study, we proposed an ANN based method to predict the occurrence of spike by using only a few voltage values at pre-spiking positions. These voltage values are taken at 1 ms apart to make simulation time step as large as possible. Then we have tested the method with various HH-type neural models. The prediction results suggest that the proposed method not only perform well in accurately predicting spike timing of neurons, but also show good generalities to different kind of neurons.

Construction of the ANN for spike prediction. The ANN used for spike prediction has three layers: one input layer with three nodes, one hidden layer with ten nodes and one output layer with one node, the adjacent layers are fully connected, as shown in Figure 1(a). The input layer contains three artificial neurons, which receive three voltage values V_1, V_2 and V_3 within an interval of 1 ms. Several artificial neurons were built in

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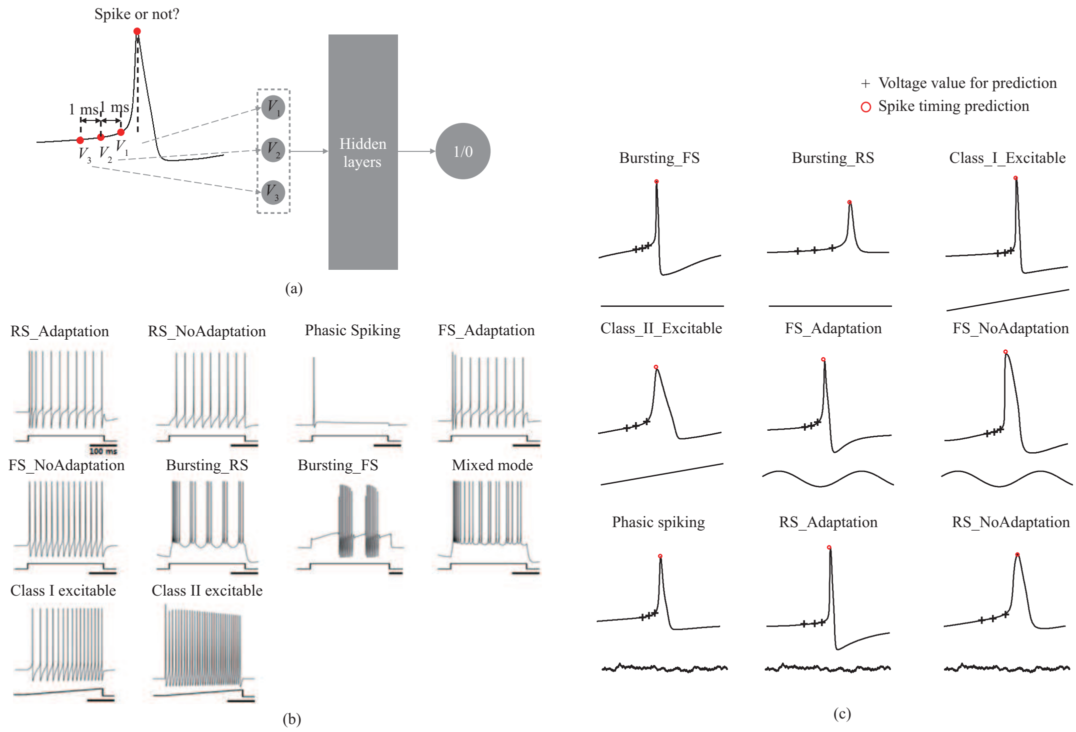

Figure 1 (a) The structure of ANN used for spike or not prediction; (b) ten typical firing patterns reproduced by nine different HH-type neuron models; (c) representative results of nine neuron models showing the performance of ANN in spike or not judgement under four current stimuli modes, black crosses denote voltage values for spike prediction, red circles present the predictive spike timing.

the hidden layers to extract features from the input layer. There is only one artificial neuron in the output layer, with the output value equals to 1 (output $\geqslant 0.5$) or 0 (output < 0.5). Sigmoid function was used as activate function, and the mean square error between real output value and expected value was selected as loss function. Construction of the ANN was realized in a Python-based package-PyBrain.

Collecting voltage samples for ANN. For each spike, a large amount of sequential voltage values V_1, V_2 and V_3 between the occurrence of previous spike and current spike were collected to build the sample dataset for ANN training and testing, and the interval between V_1, V_2 and V_3 is 1 ms. The V_1, V_2 and V_3 of 1, 2 and 3 ms before the occurrence of current spike were set as positive samples, while other groups of V_1, V_2 and V_3 were set to negative samples. Among the sample dataset, the ratio between the number of positive samples and negative samples is about 3:17 (Table S1).

To expand the application scope of our method, training samples were collected from nine different HH-type neuron models, specifically for regular spiking neuron with and without adaptation (RS_Adaptation [4] and RS_NoAdaptation [5]), fast spiking neuron with and without adaptation (FS_Adaptation [6] and FS_NoAdaptaton [7]), bursting excitatory neuron (Bursting_RS [8]), bursting inhibitory neuron (Bursting_FS [9]), phasic spiking neuron [10, 11], Class I firing excitable [12] and Class II firing excitable neuron [2]. In addition, mixed mode can also be generated by Bursting_RS under certain stimulus intensity. These ten firing patterns cover most of the firing behaviors observed experimentally in different brain regions, as presented in Figure 1(b).

To increase the stability of our method under changeable input current, two current modes including constant current and sinusoidal current were used in generating training and testing data. In addition, for testing our method under unlearnable inject current mode, two other current modes contain slope current and noise current were used in generating testing data only. In this study, voltage data of the nine neuron models were calculated in Python software using the fourth-order Runge-Kutta algorithm with step size of 0.01 ms.

Performance of the ANN in training and testing. During the training of ANN, voltage samples were first regulated to the same distribution range. Then, 70% of the total samples in dataset were randomly selected for training, among which 20% of the training data were selected for cross validation. The remaining 30% were used for testing. The initial weights of ANN were set randomly, and backpropagation algorithm was used for ANN training. As the iteration number increased, the mean square error of the ANN among nine neuron models decreased rapidly. After iteration for 1000 times, the ANN has been trained well enough.

After the training of ANN, the efficiency of our method was tested using any given V_1, V_2 and V_3 in the testing dataset. Four current stimuli modes including constant, slope, sinusoidal and noise were used to examine the performance of spike or not prediction. The ANN performs very well in spike or not judgement among nine neuron models, even under unlearned current modes (Table S2). The prediction accuracies for RS_Adaptation, RS_NoAdaptation, FS_Adaptation, FS_NoAdaptaton, Bursting_RS, Bursting_FS, phasic spiking, Class I firing excitable and Class II firing excitable neural model are 99.52%, 99.90%, 99.49%, 98.53%, 99.66%, 99.37%, 99.50%, 99.54% and 98.99%, as shown in Figure 1(c).

It should be noted that ANN is not the only choice for spike or not prediction, some other methods such as decision tree, random forest and Bayesian methods may also be effective.

Conclusion. The main finding of this study is the spike is predictable, and classical ANN can be used for spike or not judgement accurately within numerous firing patterns. This suggests that we can use relative larger time step to numerically obtain voltage data V_1, V_2 and V_3 first, then predict the occurrence of spike timing reliably. Once the prediction ANN has been trained, the prediction can be executed very fast, and hence it can be helpful to accelerate the simulation speed for complicated HH-type neuron models, especially in computing large scale neural networks.

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Supporting information Tables S1, S2. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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